A robust low cost approach for real time car positioning in a smart city using Extended Kalman Filter and evolutionary machine learning

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A robust low cost approach for real time car positioning in a smart city using Extended Kalman Filter and Evolutionary Machine Learning

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***Abstract*—A smart city is emerging as an application of information and communication technologies to mitigate the problems generated by the urban population growth. One of the smart city solutions is to establish an efficient fleet management relating to the use of a fleet of vehicles (e.g., ambulances and police vehicles). The most basic function in a fleet management system is the real time vehicle tracking component. This component is usually the Differential Global Positioning System (DGPS) or the integration of Global Positioning System (GPS) and Inertial Navigation Systems (INS). To predict the position, the Extended Kalman Filter (EKF) is generally applied using the sensor's measures and the GPS position as a helper.**

However, the DGPS high cost solution still suffers from GPS satellite signals loss due to multipath errors and the INS require more complex computing. Furthermore, the EKF performance depends on the vehicle dynamic variations and may quickly diverge because of environment changes (i.e, GPS failures by obstructions from building and trees).

In this paper, we present a robust low cost approach using EKF and neural networks (NN) with Genetic Algorithm (GA) to reliably estimate the real time vehicle position using GPS enhanced with low cost Dead Reckoning (DR) sensors. While GPS signals are available, we train the NN with GA on different dynamics and outage times to learn the position errors so we can correct the future EKF predictions during GPS signal outages. We obtain empirically an improvement of up to 95% over the simple EKF predictions in case of GPS failures.

***Keywords*—data fusion; Extended Kalman Filter; Global Positioning System; intelligent transportation systems; smart cities; Dead Reckoning; low cost; neural networks; Genetic Algorithm.**

I. Introduction

Context. A smart city takes advantage of the information and communication technologies merged with traditional infrastructures to enhance the functioning efficiency of the city, for a sustainable economic development and a high quality of life [1]. One of the major smart city initiatives is to build intelligent transportation systems (ITS) whose goal is to offer effective and energy sufficient transport services at an inexpensive cost. The fleet management solutions, among others, are integrated with the ITS to keep track of vehicles (e.g., ambulances and police vehicles) and to collect historical data of the taken paths in order to optimize the route, reduce the transportation time and conserve fuel. To reach these objectives, a real-time visibility of an accurate vehicle position is required to improve the driver safety.

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Usually, the current state of a vehicle is identified by the Global Positioning System (GPS) which is a satellite-based navigation system that provides the location, altitude and velocity at low update rates. However, the GPS performance is limited due to atmospheric disturbances, signal masking and multipath phenomenon (i.e., interference due to multiple copies of GPS signal following different paths) in areas such as tall buildings, dense foliage and tunnels [2]. One possible solution is the Differential Global Positioning System (DGPS) capable to eliminate some GPS errors by the cooperation of two GPS receivers, one remains stationary while the other is roving around making position measurements. Another feasible solution is the integration of GPS and Inertial Navigation Systems (INS) to ensure the availability and continuity of the position in an efficient manner [3]. The INS contain three accelerometers and three gyroscopes to measure the vehicle rotation rates and accelerations.

Data coming from different sensors is typically fused using the Kalman filter (KF) [4]. The filter is an optimal state estimator of linear systems start from noisy and erroneous observations. To deal with non-linear systems, the Extended Kalman Filter (EKF) is adopted through a linearization procedure using Taylor series expansions.

Problem. The multipath errors remain to the detriment of DGPS high *cost* solution. Furthermore, the INS impose restrictions on the environments where they are implemented because of their computing *complexity*, and the high performant inertial sensors are very *expensive* [5].

The KF performance requires sufficient a priori information of system noises and measurement errors, also it depends on how the system and measurement dynamics are correctly modeled. This is why the KF predicted position tends to quickly *diverge* when GPS outage occurs.

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Contribution. In this paper, we propose a new robust low cost approach for real time car positioning in a smart city using EKF and Evolutionary Machine Learning. The low cost comes from the use of the GPS enhanced with Dead Reckoning (DR) sensors (only an odometer and a gyrometer) which are easy to use and keep the calculations simple. The robustness of our approach stems from our use of neural networks (NN) to learn the EKF position error during GPS signal presence. The NN estimate the EKF predictor error during GPS signal outage, allowing the system to correct the EKF estimation and preventing it from divergence. We use Evolutionary Algorithms, namely Genetic Algorithm (GA) in the training phase of NN.

Contents. This paper is organized as follows. In Section II, we discuss some selected works related to this topic. We present the essential background on EKF, NN and GA in Section III. Then, we provide the formulation of our suggested approach in Section IV. In Section V, we detail the experimental results.

II. Related Works

Various research investigations related to vehicle positioning suggest the integration of GPS and DR sensors like odometers and gyrometers, among which are [6] and [7]. The odometry information provides the distance travelled by the vehicle, thus its speed and the gyrometer measures the angular velocity. Despite their autonomy and independency of any signal blockage, these sensors are subject to time growing errors such as bias drift and scale factor change. Consequently, such combined system GPS/DR takes advantage of DR short-term stability and GPS long-term reliability. It helps, when GPS is available, to keep down the odometer and gyrometer errors in real time and ensures a continuous positioning during the GPS signal outages.

Lucet et al. [6] employ the EKF for the fusion of data from GPS and a low cost DR system. However, the loss of GPS signal for long periods reduces the filter accuracy and even causes its divergence. In their work, El-Sheimy et al. [8] propose two architectures: the position update architecture and the position and velocity update architecture for vehicular navigation. Both of them use the multilayer feed-forward NN with backpropagation learning algorithm as the core algorithm to integrate data from INS and DGPS and to mimic the dynamical model of the vehicle. In [9], Asadian et al. introduce an adaptive neuro-fuzzy inference system with a genetic optimization algorithm to combine data from INS and GPS. This network is trained during the availability of GPS signal so to predict the error of the INS position components during GPS signal blockage.

Unluckily, substituting the EKF entirely with NN can be a non-optimal solution: these networks require a learning phase and their estimation quality can only be guaranteed if the trained data are sufficient. Goodall et al. [10] claim that the use of NN with backpropagation learning algorithm can bridge the gap in the EKF prediction mode based on data from GPS and INS. While GPS is available, the NN are trained on different samples to learn the position errors, so they can correct the additional EKF drifts during GPS signal loss.

III. Background

In this section, we cover the background of the EKF, NN and GA.

A. Extended Kalman Filter

The EKF is a non-linear version of the KF that linearizes the process and measurement models about the current mean and covariance. The filter is a set of mathematical equations which uses the process model to estimate the current state of a system, then a correction of this estimate is performed using any available sensor measurements.

1) Modeling: Let us consider a car-like model of a front-wheel drive vehicle. The origin M of the body frame (rigidly attached to the vehicle) is located midway the rear axle while the x-axis is aligned with the vehicle longitudinal axis (see Fig. 1). For the vehicle dynamics analysis, the North-East-Down frame known also as a navigation frame is used; so any movement related to the body frame have to be converted to the navigation frame.

The kinematic equations mentioned below describe the vehicle position denoted by (N,E,ψ) where N and E denote the north and east components and ψ represents the heading [6]:

$$\begin{cases} N_{k+1} = N_k + ds_{k+1}.sinc(\frac{d\psi_{k+1}}{2}).cos(\psi_{k+1} + \frac{d\psi_{k+1}}{2}) \\ -d\psi_{k+1}.(D_x.sin(\psi_k) + D_y.cos(\psi_k)) \\ E_{k+1} = E_k + ds_{k+1}.sinc(\frac{d\psi_{k+1}}{2}).sin(\psi_{k+1} + \frac{d\psi_{k+1}}{2}) \\ +d\psi_{k+1}.(D_x.cos(\psi_k) - D_y.sin(\psi_k)) \\ \psi_{k+1} = \psi_k + d\psi_{k+1} \end{cases} \tag{1}$$

where

- ds_{k+1} is the distance traveled by the vehicle between k and k+1;
- $d\psi_{k+1}$ represents the heading variation corresponding to the angular velocity between k and k+1;
- D_x and D_y are the distances in the body frame between the GPS antenna and the middle of the rear axle.

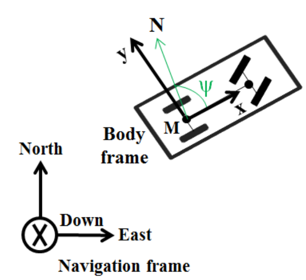

Fig. 1. Vehicle Kinematic Model

2) Prediction and Correction Phases: Fig. 2 shows a scheme for the KF model. In our case, the state vector at time epoch k is X_k=(N_k,E_k,ψ_k) and the measurement vector is Z_k= (N_{GPS_k},E_{GPS_k}). Before the estimation process starts, values for the initial state $\hat{X}_0^+$ and the corresponding error covariance P_0^+ are assumed to be known. The prediction mode starts by projecting the state and error covariance ahead to estimate $\hat{X}_k^-$ and P_k^-. When new GPS measurements are available at time epoch k, the filter starts the update mode. At this stage, the Kalman gain K_k, updated state $\hat{X}_k^+$ and error covariance P_k^+ are computed.

B. Neural Networks

NN are a subset of Machine Learning methods attempting to mimic the structure and operation of the human brain. A neural network acts as a massively parallel distributed processor that use flexible computing paradigms to solve complex and uncertain problems [11]. NN are composed of many interconnected processing elements called neurons linked by synaptic weights. The arrangement of neurons into layers and the connection strengths within and between these layers refers to the network architecture.

In many practical applications, the most used model is the multilayer feed-forward NN in which all signals flow in one direction; from the input layer to the output layer passing by one or more hidden layers. In order to train the NN, weights of each unit are adjusted in accordance with weight optimization algorithms like GA.

C. Genetic Algorithm

GA is a class of Evolutionary Algorithms used to find exact or approximative solutions to optimization and search problems [12]. It is a stochastic search algorithm that simulates the procedures of biological evolution and natural selection. To accomplish this task, GA represents a problem by a population of individuals, also called strings or chromosomes, considered as potential solutions. Each chromosome is composed of genes which control the inheritance of one or several characters [13].

The flexiblity of GA facilitates the connection weights optimization in the training phase of NN [14]. For this, an initial parent population of chromosomes is generated randomly and the genes are the NN weights to learn. Then, each individual is evaluted based on a user-defined fitness function and only individuals with better performance are selected to reproduce. Once this has been done, selected parent solutions are crossed over to form new offsprings; then a random mutation is applied to each offspring according to a small probability. The evolution process is repeated until a maximum number of generations is reached or a fitness level is satisfied [13].

IV. Formulation of the hybrid EKF/NN approach

In this section, we present a possible vehicle prototype and the formulation of our suggested approach in both the training and prediction phases. The prototype is not yet implemented, however we conducted extensive simulations on the Institut Pascal Data Sets [15] that were collected using VIPALAB, a platform equiped with multiple sensors. We have improvements over the EKF solution between 53% and 95%.

A. Possible Vehicle Prototype

Fig. 3 illustrates the positions of the GPS and the odometer/gyrometer sensors in our possible vehicle prototype; each one of them is coupled to an Arduino nano and a Xbee module. The Arduino nano is dedicated for the treatement while Xbee module ensures a Zigbee communication for the wireless sensor networks. For the data treatment, a Raspberry with Xbee communication module is mounted on the car's dashboard. Our vision then is to support a real implementation of this prototype.

B. Training Phase

In general, the odometer bias or gyrometer drift consists of deterministic and stochastic parts. The former can be removed by calibration procedure while the latter is not easy to handle due to its random nature. Accordingly, the EKF performance depends on how the sensor components are correctly modeled; though a perfect tuning of the filter is rarely achieved since

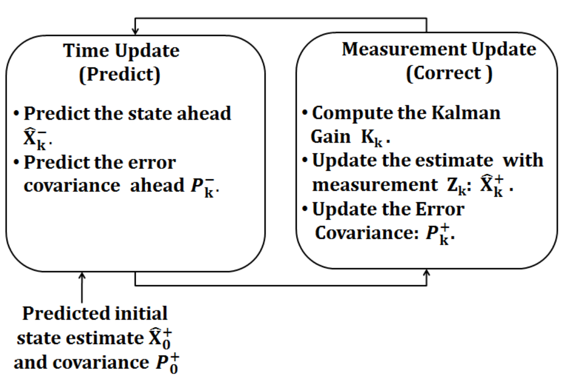

Fig. 2. Kalman Filter Model

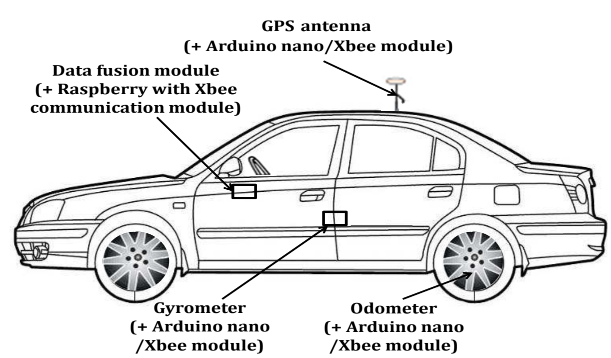

Fig. 3. Wireless sensor network

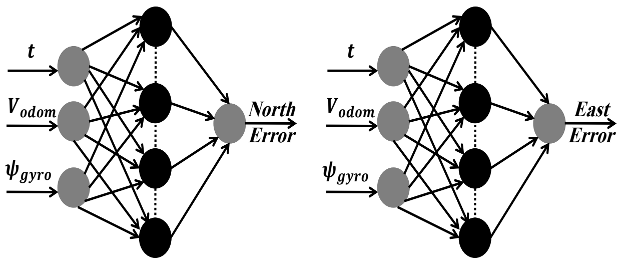

Fig. 4. North and east networks architecture

vehicle dynamic variations and environment changes occur oftenly. As a consequence, the EKF performs badly during GPS signal blockage which may result in its divergence.

To circumvent the EKF deficiencies, NN are a natural choice that require no calibration or modeling procedures. The networks are used to estimate the time-correlated position errors during the EKF prediction phase when no GPS signal is available. Two three-layer feed-forward NN are trained on different dynamics using GA, so they can help to predict the north and east error drifts.

To fully represent the vehicle dynamics, the NN inputs consist of vehicle velocity, heading angle and time elapsed since last GPS measurement. The networks outputs are north and east errors which are compared to desired position errors. Fig. 4 shows the north and east networks architecture.

For training the NN, the target values used are computed as a difference between positions provided by two parallel EKFs. One filter provides a reference vehicle position while the other gives a predicted one by removing intentionally the GPS signals [10]. It should be noted that the training procedure presented in Fig. 5 is executed at the GPS sampling rate.

C. Prediction Stage

After training on different dynamics and outage times, the networks are used in prediction mode to help compensate for real GPS outages. The inputs are sent to the networks which

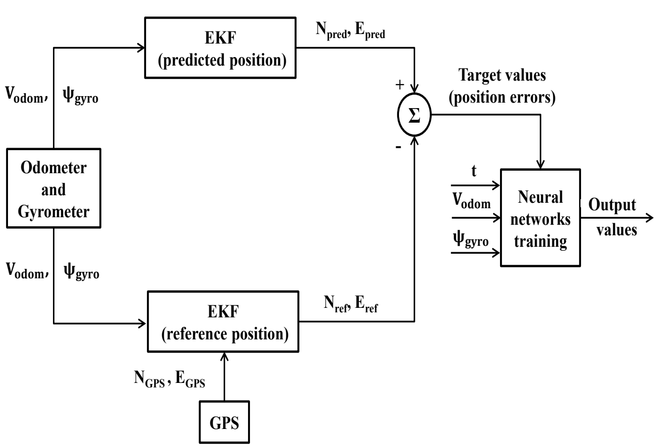

Fig. 5. NN training phase

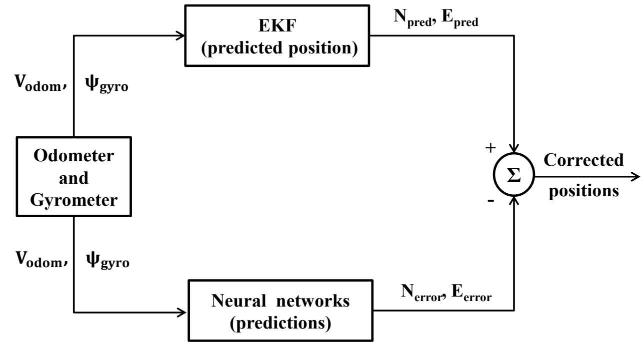

Fig. 6. NN testing phase

provide estimates for the position errors along the north and the east directions. Since the EKF predictions without GPS measurements update contain errors, they are compensated by the networks outputs to form the corrected positions. The testing procedure is shown in Fig. 6.

V. Experimental Tests and Results

In this section, we present the test vehicle prototype and the simulation results of our suggested hybrid approach.

A. Test Vehicle Prototype

The performance of our proposed hybrid technique was examined with the Institut Pascal Data Sets [15]. The field test data were collected using VIPALAB, a platform equiped with multiple sensors. In our case, the test system comprises three sets of an uBlox-6T-0-001 GPS receiver, an odometer and a Melexis MLX90609-N2 gyrometer. GPS values were collected at the frequency rate of 1 Hz while the odometer/gyrometer data at 50 Hz. The road test trajectory used is CEZEAUX-Heko (given in Fig. 7) which spans over a distance of 4.2 km during 28 minutes.

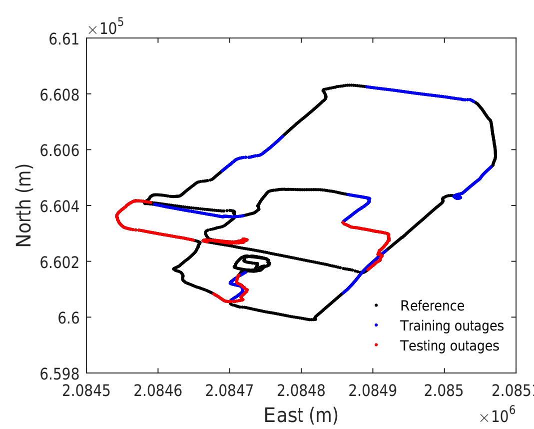

Fig. 7. Field test trajectory

B. Simulation Results

To examine the performance of our proposed approach, the field test data were divided into two parts. During the first 19 minutes, a total of seven GPS simulated outages (shown in Fig. 7) are used to train the networks. Each outage lasts 60 seconds to leave the EKF position errors enough time to diverge. For the last 9 minutes, the NN run in the testing mode to generate predictions of the position drifts.

The NN are trained using batch-incremental approach. For every outage, a set of new inputs/targets are presented to train the NN using GA to learn the network weight parameters. The objective is to reduce the mean squared error (MSE) between the networks outputs and the desired values (see Fig. 5). In our case study, the north and east networks architecture chosen emprically consist of 3 inputs, 5 hidden neurons and one output while the training goal is to reach MSE less than 10^{-4}m^2 given the real time constraints. Fig. 8 show the results of the training outages while the time intervals between them are masked. It appears clearly that the outputs of north and east networks are very close to the target values.

To investigate the performance of this hybrid method, the GPS data were intentionally removed since there were no natural GPS outages in the field test. The networks can then be used to provide predictions of position drifts to correct the EKF predictions. For this purpose, they generate outputs based on dynamic inputs and latest estimated weight parameters. Relatively, results of the GPS test outages (presented in Fig. 7), with period lengths of 90 and 60 seconds, are given in Fig. 9.

To compare the estimated position by our proposed approach and the one of EKF, two different evaluation indicators are calculated for each outage: the root mean square error (RMSE) and the mean absolute error (MAE). They are expressed by the following formulas:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(A_k - F_k)^2} \qquad (2)$$

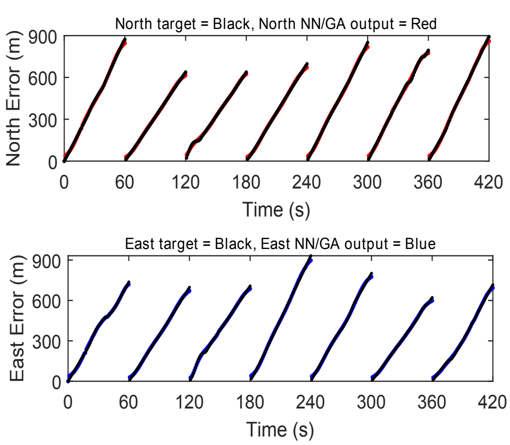

Fig. 8. North and east networks training results using GA

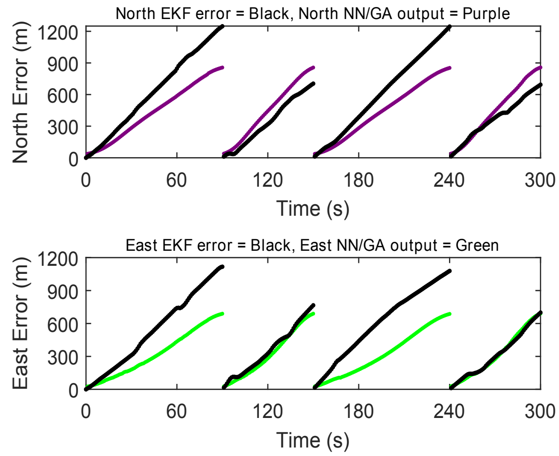

Fig. 9. North and east networks testing results using GA

$$MAE = \frac{1}{n}\sum_{k=1}^{n}\left|A_k - F_k\right| \qquad (3)$$

where A_k is the actual EKF updated position by GPS measurements at time epoch k, F_k is either the EKF predicted position or the EKF corrected position by NN while n is the total number of predictions. These results are listed in Tables I and II for north and east position components. By combining EKF and NN together, the results show a significant decrease in RMSE and MAE over the EKF method. This hybrid approach enhances the vehicle position accuracy over the EKF predictions during GPS outages.

TABLE I
IMPROVEMENT OVER SIMPLE EKF OF NORTH POSITION ESTIMATE USING OUR APPROACH DURING TEST OUTAGES

	EKF		Our approach (EKF/NN)		Improvement (%)	
Outages	RMSE (m)	MAE(m)	RMSE (m)	MAE(m)	RMSE (m)	MAE(m)
Outage 1	732.47	630.57	221.02	191.12	69	69
Outage 2	408.82	343.18	111.47	103.59	72	69
Outage 3	715.54	613.58	205.05	174.60	71	71
Outage 4	418.99	372.16	104.55	83.01	75	77

TABLE II
IMPROVEMENT OVER SIMPLE EKF OF EAST POSITION ESTIMATE USING OUR APPROACH DURING TEST OUTAGES

	EKF		Our approach (EKF/NN)		Improvement (%)	
Outages	RMSE (m)	MAE(m)	RMSE (m)	MAE(m)	RMSE (m)	MAE(m)
Outage 1	640.44	545.17	253.56	218.90	60	59
Outage 2	419.84	359.72	39.98	36.83	90	89
Outage 3	681.06	606.22	302.99	280.48	55	53
Outage 4	377.17	319.96	18.25	15.24	95	95

VI. Conclusion

In this paper, we present a hybrid *robust* approach to continuously estimate the real time vehicle position based on data coming from a GPS and *low cost* DR integrated sensors; so that it can be used by different fleet management applications in the context of a *smart city*. We propose the combination of EKF and NN based on GA to overcome the EKF drawbacks when no GPS signal is detected. The NN, after being trained on different dynamics and outage times, are used to correct the EKF errors that grow largely during GPS outages. Experimental results with field test data demonstrate the ability of feed-forward NN with GA to learn and make reasonable predictions of EKF drifts during different GPS blockage periods.

Future Work. Empirical results with simulated GPS outages showed very promising progress. Nonetheless, real GPS outages are more complex and not easy to handle due to the GPS quality degradation. Further investigation is then needed to test and improve this hybrid solution during real GPS outages, that is why we intend to implement our vehicle prototype in future related works.

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